# COVID-19 and Supply Chain Disruption: Evidence from Food Markets in India†

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This paper looks at the disruption in food supply chains due to COVID-19 induced economic shutdown in India. We use a novel dataset from one of the largest online grocery retailers to look at the impact on product stockouts and prices. We find that product availability falls by 10% for vegetables, fruits, and edible oils, but there is a minimal impact on their prices. On the farm-gate side, it is matched by a 20% fall in quantity arrivals of vegetables and fruits. We then show that supply chain disruption is the main driver behind this fall. We compute the distance to production zones from our retail centers and find that the fall in product availability and quantity arrivals is larger for items that are cultivated or manufactured farther from the final point of sale. Our results show that long-distance food supply chains have been hit the hardest during the current pandemic with welfare consequences for urban consumers and farmers.

*Key words*: COVID-19, food, online retail data, prices, supply chain disruptions.

*JEL codes*: E20, E30, Q11, L81, Q54.

The COVID-19 pandemic has emerged as a significant health risk, and countries around the world have responded with partial shutdowns of their economies to slow the pace of infections. These measures have reportedly led to massive disruptions in global and domestic supply chains. The restoration of supply chains to their pre-lockdown levels will require prompt policy intervention. In this context, the vulnerability of food supply chains to disruptions needs special policy focus. Any disruption in food availability has adverse health consequences through a reduction in diet diversity and nutritional intake, which can further increase people's susceptibility to infection (Short, Kedzierska, and van de Sandt 2018 and Anríquez, Daidone, and Mane 2013).[1] Reduced food availability with unmet demand could also result in price spikes (FAO 2020). Both have important welfare implications, especially for poor households.

Consequently, an essential question for public policy is to measure the level of these disruptions and where they are more likely to occur (Inoue and Todo 2020 and Barrot, Grassi, and Sauvagnat 2020). Stringent lockdowns or a protracted epidemic can affect food supply in many ways. First, it can directly impact the transportation of food products. Second, it can impact the availability of packaged goods from food-processing industries as manufacturing activity slows down due to social distancing guidelines and labor shortages. Third, it can reduce future agricultural production by reducing current incomes.[2] These issues are more salient in a

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[1] One of the critical lessons from the Spanish Flu of 1918 is that populations with severe malnutrition are more vulnerable to disease. For instance, Short, Kedzierska, and van de Sandt (2018) find that influenza-related mortality was higher in regions of India having greater malnutrition.

[2] Evidence from Ebola epidemic in Africa shows that restrictions on movements can lead to disruptions in food supply chains and eventually reduce production, and adversely affect food security (FAO 2020).

developing country context where food supply chains are long and fragile (Reardon et al. 2020 and Aggarwal 2018), and millions live under poverty. Given this background, we quantify the level of disruption in the food supply chains in India due to COVID-19 induced lockdown.[3]

We do this exercise by using data on food availability at the retail and the farm-gate level. Among all countries, India implemented one of the most stringent lockdowns to contain COVID-19, which could have put a strain on its supply chains.[4] The first nationwide lockdown was announced on March 24, 2020, and lasted until April 14, 2020. The first lockdown was unanticipated, in terms of timing, stringency, and duration. It curtailed all economic activities, including transportation of goods, except those deemed essential like food and medical supplies. The reduction in freight services combined with the restrictions on interstate transportation could have disrupted the food supply chains, with a larger impact on products that are procured from far. We test this hypothesis by combining the food availability data with distance to production zones from the retail centers (cities).

On the retail side, our data on product availability and prices come from one of the largest online grocery retailers in India. The data are scraped daily and provide information on product stockouts and sale price for in-stock products.[5] Overall, we track 789 products across three cities. We evaluate the impact across four product categories, vegetables and fruits, that is, perishables; and edible oils, cereals, and pulses, that is, non-perishables. We employ an event study framework to study the change in product availability and prices, using data for approximately twenty days before and after the first lockdown, which came into effect on March 25, 2020 (within four hours of the announcement). An event study framework can be used to obtain consistent estimates in this case because the exact date, severity, and geographic coverage of the lockdown were unknown. Additionally, we observe availability and prices at the product level, which allows us to control for time-invariant product characteristics.[6] On the farm-gate side, we use data on daily quantity arrivals of commodities (only vegetables and fruits) in the primary agricultural markets called *Mandis* to conduct a similar exercise.

We find that the online product availability of vegetables and fruits falls by 8%, whereas it falls by 14% for edible oils. The impact on cereals and pulses is less pronounced. Because we capture the fall in product availability on the extensive margin, that is stockouts, these results are likely to be a lower bound on the total fall in available product quantity. This is supported by the results based on *Mandi* data, where the quantity arrivals for vegetables and fruits fall by 20% for these cities.[7] At the same time, there is minimal change in online prices for all categories. Online prices are easy to monitor, and Indian government had issued guidelines against price gouging during the lockdown, which may explain the inaction on online prices. Because the online retail data are from an online grocery retailer and not an online platform that serves to aggregate sellers like Amazon, our results are similar to Gagnon and Lopez-Salido (2020) and Cabral and Xu (2020), who also see minimal change in prices during such events for existing sellers. They argue that monitoring and fairness concerns can drive pricing decisions. In fact, the online retailer in our study is a long-term player in the market, hence its decision to not engage in price gouging can also be aligned with its long-term strategy of capturing market share, which could be adversely affected if it engaged in price gouging. These results lead us to the next question, why do we see a fall in the availability of products or increased stockouts?

First, as a direct test of the supply chain disruption, we examine if the fall in availability is more pronounced for products whose production zone is farther spatially. There were media reports on a collapse in daily truck movement during the lockdown, as the state governments implemented strong border controls.[8] We thus hypothesize that

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[3]In 2018, India ranked 103 among 119 countries in the Global Hunger Index (GHI). Around 270 million people were living living under poverty in India in 2011–2012.

[4]The total COVID-19 cases in India were less than 500 when it imposed the first lockdown.

[5]This data are being collected on an ongoing basis by the author, Shekhar Tomar, and hence predates the spread of COVID-19.

[6]We use precise product level information, both before and after the lockdown, which allows a more uniform comparison. Such a comparison is not possible with standard datasets collected by government agencies. Department of Consumer Affairs, India collects data on daily retail and wholesale prices. However, it does not report product level information.

[7]There were many media reports on reduction in arrivals in primary agricultural markets in India. Source: The Wire.

[8]State governments closed down inter-state borders and thoroughly inspected vehicle movement during the first lockdown. Report Times of India.

transportation bottlenecks are likely to be larger for long-distance freight. To test this, we supplement our retail and farm-gate data with distance to production from each retail center. For edible oils, we use the exact distance between the closest manufacturing plant for each edible oil product–city pair. For vegetables and fruits, we construct an inverse distance index because their production is geographically dispersed across the country. In both cases, the fall in availability is higher for products produced farther from the retail centers (cities). In fact, in the case of *Mandis*, the entire fall in quantity arrivals is driven by commodities coming from far. These findings suggest that distance of retail center to production zone can be critical for food availability during a pandemic.

Next, we look at the demand side. Because online grocery platforms in India cater to middle-upper income households, it is unlikely that their incomes were hit in the immediate aftermath of the lockdown. So, the retailer reducing product availability due to lower demand is unlikely. The other potential demand channel leading to stockouts could be panic buying by the customers. Although some panic buying can occur, even for online market under consideration, but that is not the primary driver of our results. We address this concern in five ways. First, the lockdown was unanticipated, as discussed in detail in the next section. It was announced on the evening of March 24 and came into force within four hours. If there was anticipation that such an extreme measure would be taken by the government, panic buying in online retail markets would have fructified before the lockdown. We test for pre-trends and do not find any fall in availability in the week before the lockdown.

Second, logistical delivery constraints faced by online retailers preclude panic buying because unlike brick and mortar shops, where individuals could visit and buy in store, online groceries had to be delivered by personnel. E-commerce deliveries during the lockdown were allowed only through personnel having curfew passes, which took a few days to arrive post the first lockdown.[9] The number of delivery personnel available with the e-retailer were also fixed as new personnel could not be hired and trained to meet the surge in demand in online food market, in the immediate weeks after the first lockdown. Third, we show fall in availability for vegetables and fruits, which are unlikely to be stockpiled by households due to their perishable nature. If our results were only driven by panic buying then we should have observed a greater fall for non-perishables. Fourth, we test for fall in commodity arrivals in wholesale markets for vegetables and fruits, which are unlikely to be driven by panic buying by households.

Last, we find a greater fall in products that traveled farther to the retail cities, in both online and wholesale markets. These also point toward supply chain disruptions rather than panic buying. If only panic buying and no disruption in supply chains were driving our results, then products procured from far would not see a higher decline in availability. We further look at persistence in our results. We find that the availability of non-perishables bounces back after the end of the first lockdown, whereas the availability of perishables continues to remain low in the online data. The farm gate quantity arrivals of the perishables also continue to remain lower than their pre-lockdown levels. This again points to supply chain disruptions, which are likely to be larger for perishables because they are at a higher risk of spoilage than non-perishables, due to below normal operation of freight services.

We make several contributions to the literature. First and most generally, our work is closest to the studies that look at the impact of natural disasters like earthquakes, hurricanes, and snowstorms (Cavallo, Cavallo, and Rigobon 2014, Heinen, Khadan, and Strobl 2019, and Gagnon and Lopez-Salido 2020) on product availability and prices.[10] However, there are two key differences between COVID-19 induced lockdowns and such disasters. Most disasters are local and can have a heterogeneous impact on demand, based on location. They may or may not cause supply chain disruption depending on the extent of the area affected by the shock. Also,

[9]See: Indian Express Report. Panic buying reports came in largely from brick and mortar stores like supermarkets and that too for non-perishable items. See: The Hindu

[10]Cavallo, Cavallo, and Rigobon (2014) examine the effects of earthquakes in Chile and Japan on product availability and prices using online data. Heinen, Khadan, and Strobl (2019) evaluate the impact of hurricanes and floods in the Caribbean using monthly Consumer Price Index (CPI) data, whereas Gagnon and Lopez-Salido (2020) use scanner data to study the impact of natural disasters in the US. Bellemare (2015) uses natural disasters to generate exogenous shifts in food prices to study the impact of food prices on social unrest.

for disasters like hurricanes and snowstorms, their occurrence and the resultant length of disruption can be predicted based on past experiences, leading to large anticipatory effects. Thus, the effect of lockdowns due to COVID-19 on product availability and prices can be different. In a recent paper, Cabral and Xu (2020) look at price gouging in China for medical supplies like masks and sanitizers. Our work directly contributes to this nascent literature that evaluates the effect of COVID-19 on product supply and prices.

Second, we study this question by using online retail data in conjunction with farm-gate arrivals. Thus, we combine multiple data sources in our analyses. Online retail data collection has been gaining traction over time for analyzing inflation trends (Cavallo and Rigobon 2016 and Cavallo 2018). Previously, Cavallo, Cavallo, and Rigobon (2014) have used it to study the impact of earthquakes in Chile and Japan. They find a reduction in product availability but relatively stable prices, similar to what we find for India. In this context, we show how online data can be useful for policymakers to infer impact on a real-time basis, even in a developing country setting. This is highly relevant as the current pandemic has also upended the existing data collection systems in the developing countries, which mostly rely on physical data collection. For instance, the National Statistical Office (NSO) in India deferred the release of inflation numbers for April 2020, as the lockdown affected the official price collection exercise.[11] Last, our work is connected to the literature that looks at how supply chain disruptions propagate. Carvalho et al. (2016) provide evidence for the role of input–output linkages in supply chain disruptions after the Great East Japan earthquake using firm-level data. We extend this work by highlighting the importance of spatial inter-connections and showing how the distance between production and final point of retail sale can dictate the impact on supply chains.

Our findings have important policy implications. We demonstrate that the supply chains for perishables are the most vulnerable to the current lockdowns. These have important welfare consequences for consumers and producers. While product availability falls for urban consumers, it leads to income losses for farmers. Moreover, this impact on farmers is more pronounced for those located farther from retail centers. Our results suggest that removal of barriers to interstate trade in food and monitoring of long-distance freight will aid in post-lockdown economic recovery. The rest of the paper is organized as follows. We describe the context in Section 2 and the data in Section 3. The empirical strategy is presented in Section 4. The main findings are discussed in Section 5, and Section 6 provides robustness checks. Section 7 gathers concluding remarks.

## Background

The first lockdown in India was announced on March 24, 2020 and came into force from the midnight of March 25, 2020, until April 14, 2020. The lockdown was further extended multiple times until May 31, 2020, with staggered relaxations post-April 20, 2020. Although the later lockdowns were anticipated, the geographical coverage of the first lockdown as well as the timing came as a surprise and was unanticipated. India closed down most economic activities across all regions at the same time, although the COVID-19 cases were present only in a few areas. An analysis based on OxCGRT data also shows that among the sixty-one countries that imposed a greater than 90% stringency until June 2020, India was one of the first few to implement it in the month of March 2020. In fact, the number of confirmed COVID-19 cases was around 500 among India's 1.3 billion population when the first lockdown was implemented. Thus, the timing of the first lockdown, and more so the extent of its severity, were unanticipated.

The lockdown in India was one of the most stringent. Figure 1 compares the mean stringency of economic lockdown and COVID-19 infections across countries, based on the data from OxCGRT (Hale et al. 2020). It shows that the mean stringency enforced by India was one of the highest relative to its number of COVID-19 cases (high mean stringency index implies more severe lockdown). Balajee, Tomar, and Udupa (2020) show that India's stringency measures were the harshest for its given number of COVID-19 cases in the first phase of lockdown. India gets a high value on the stringency index because it curtailed most economic activities, except those deemed essential like food and medicine. The state

[11] To study the level of disruption in economic activity due to COVID-19, there are efforts to collect novel datasets with high frequency (Chetty et al. 2020) even in advanced economies.

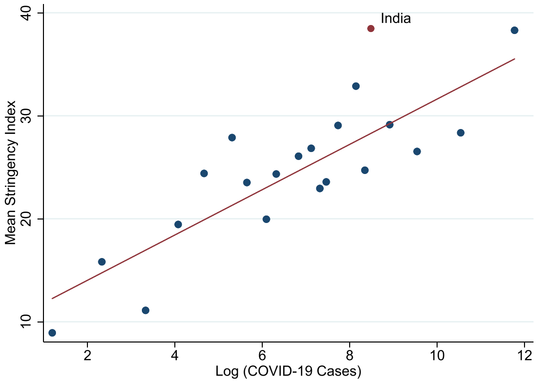



**Figure 1. Mean stringency vs. log (COVID-19 cases)**

*Notes*: The figure gives bin-scatter based on data until April 16, 2020. The x-axis is based on log (COVID-19 cases), and the y-axis corresponds to Mean Stringency Index for 106 countries. The figure shows India as an outlier as its mean stringency is much higher relative to countries with a similar number of confirmed cases. Data Source: OxCGRT.

governments also enforced border controls, which led to restricted movement of goods. The decline in overall freight services could have impacted even the transport of essential goods.

In such a situation, the lack of adequate warehousing facilities in India would have worsened the food supply situation, especially for perishables. According to the Central Institute of Post-Harvest Engineering and Technology (CIPHET), the inadequacy of warehousing facilities in India leads to an annual wastage of 16% in vegetables' and fruits' produce value.[12] The food supply chains in India are long as they operate along the rural–urban geography. These are dominated by private players because 95% of all purchased food is sold by the private sector (Reardon and Minten 2011). Inadequate warehousing is then likely to lead to greater spoilage if supplies fail to reach the urban markets.

Last, we discuss the role of online market in India. The landscape of food supply chains has been undergoing a rapid change in India, with an increase in modern retail sales (Reardon and Minten 2011). The share of online grocery retail in India has also been increasing at a fast pace. Although it constitutes a small proportion of the total urban and rural grocery sales market in India, it is likely to be highly penetrated in the metropolitan cities under consideration in this paper. Moreover, it has witnessed high growth in recent years (106% growth rate in 2019–2020 according to RedSeer 2019). Additionally, given similar intermediate feeder supply chains, the online and the offline markets are interlinked. Past data show that prices in offline and online data co-move and the latter can be used to track inflation (Appendix figure A.1).[13] Thus, reduction in supplies is likely to hit both the online and the offline retailers, though the magnitudes may differ. The effect on online retailers can be smaller due to distributor linkages, which make their supply chains more resilient. An average offline store is very small in India and cannot match the supply-chain infrastructure of this online retailer. Hence any evidence of disruption in online data points at a bigger crisis in the offline retail sector. Therefore, we supplement the online retail data with data from wholesale food markets in India to provide additional evidence in support of supply chain disruptions.

## Data

We collect *online data* on product availability and prices from one of the biggest online grocery retailers in India (details in Appendix A). This online grocery delivery firm holds 70% of the online grocery retail market share. It is important to note that unlike big retailers, like Amazon, which sells all types of products and mainly provides a platform to small retailers, this retailer specializes in grocery delivery and has its own supply chain, akin to big brick and mortar stores. The orders can be placed through the retailer's website or a mobile phone application. We use daily data on products available for sale from March 1, 2020– April 13, 2020, which capture information on the product name, sale price, and discount offered, for three cities: Delhi, Chennai, and Kolkata.[14] We include four categories

[12]India has a cold storage capacity of 35 MT (Ministry of Food Processing Industries) across 7600 cold storage facilities, but 75% of storage is for potatoes. Also, most cold storage facilities are usually built in the regions where these crops are cultivated (e.g., Uttar Pradesh for potato and Maharashtra for onions have some of the largest capacities in these crops). Source: CIPHET.

[13]Banerjee, Singhal, and Subramanian (2018) use it to predict the state-level food inflation using data from one city.

[14]We drop the day just after Holi (March 11) because the wholesale markets were shut on Holi affecting retail sales on the next day and the day of first public curfew in India (March 22). Thus, the number of days in the pre-lockdown period in the data is twenty-two. The number of days in the post lockdown period is eighteen, after excluding March 29 and March 30, the dates for which data could not be scraped.

of food products in our analyses: vegetables and fruits, edible oils, cereals, and pulses. These four categories together comprise 25% value of the urban consumer basket and 65% value of the total food basket in urban India. These proportions are based on the commodity weights in the Consumer Price Index for India (2013).

Within the category of vegetables and fruits, we restrict our analyses to twenty-two major commodities. Each of these commodities contributes at least 0.1% value of consumer basket and together constitute 85% of the vegetables and fruits basket in India.[15] In the online data, multiple products can lie within a commodity, for example, *cabbage* may be of two types—green cabbage and red cabbage. In our analyses, green and red cabbage will be products that are part of the commodity named *cabbage*. Most commodities have one to seven products (Appendix figure C.1 gives frequency distribution). Within the categories of edible oils, cereals, and pulses, we use all available products. Table 1, Panel (a) shows the mean daily product availability (column (2)) and total products (column (6)) for each product category during the entire period. Table 1, Panel (b), reports the mean product availability in the period before and after the lockdown. It shows that the mean availability for vegetables, fruits, and edible oils falls post the lockdown but not for cereals and pulses.

In addition to the online retail data, we also use data on commodity quantity arrivals for vegetables and fruits in the primary agricultural markets, called *Mandis*.[16] In India, *Mandis* are the markets where farmers sell their produce to the intermediaries, and can be used to gauge farm-gate arrivals. Given the nature of the products sold in the *Mandis*, our analysis is restricted to fruits and vegetables. We use daily data on quantity arrivals at the commodity level in the *Mandis* from March 1–April 13, 2020. This is done for two of the three cities included in our main analyses—Delhi and Kolkata—because the data for the third city, Chennai, have not been updated for recent months. The data are aggregated across all *Mandis* in each city. There are five primary *Mandis* in Delhi and three in Kolkata. For comparability, we keep the same set of twenty-two commodities as in our main analyses using the online retail data.[17] Unlike the online data, we do not observe the exact product within a commodity in *Mandi* data. Hence, our analysis is restricted at the commodity level. Table 1, Panel (c), reports the mean quantity arrivals (in tonnes) in the period before and after the lockdown. The difference between the two means shows that the quantity arrivals for vegetables and fruits falls by sixty tonnes on an average across *Mandis* post the lockdown. In the case of prices, *Mandi* data are available only for Kolkata and for a limited number of commodities, and hence, we exclude it from the main analyses.

We supplement the above datasets with distance to the manufacturing plant/production zone. We hand collect the data on the nearest manufacturing plant for different edible oil brands present in each city (we can map 93% of the total products under edible oils). We are unable to collect this data for cereals and pulses, as a significant number of products are sold under retailers' own brand name, and the plant information is not available in the public domain. For vegetables and fruits, individual products cannot be mapped to a manufacturing plant. Instead, we use state-wise aggregate horticulture production from the Ministry of Agriculture for the most recent year 2017–18 to construct a production-weighted distance index (Ministry of Agriculture & Farmers' Welfare 2018). Finally, we use Google API to calculate the road distance, in kilometers, between our cities and actual plant location, in the case of edible oils, and state capitals, in the case of vegetables and fruits.

## Empirical Strategy

We use an event study design to evaluate the impact of the first lockdown on online product

[15]Appendix Figure C.1 shows the product distribution for the eighteen commodities (out of the twenty-two commodities) present in the online data. Chilies, lemon, ginger, and garlic also contribute more than 0.1% of the CPI basket but are dropped from our analyses due to insufficient online availability in the pre-lockdown period.

[16]*Mandis* are also referred as Agricultural Produce Market Committees. See Chatterjee (2019), Narayanan and Tomar (2020), and Banerji and Meenakshi (2004) for details about the organization of agricultural trade in India and the role of *Mandis*. The data for quantity arrivals for various commodities is available at http://agmarknet.dac.gov.in.

[17]The data include the eighteen commodities in our main analysis and four more—chillies, lemon, ginger and garlic—which were excluded from the online availability analyses due to insufficient observations. We drop the day of Holi (March 10) because the *Mandis* were shut that day and the day of first public curfew in India (March 22). The final set includes twenty-two commodities whose data were available for forty-two days in each city = 924 observations.

**Table 1. Summary Statistics**

Panel (a): Online product availability

| Category | Observations (1) | Mean (2) | Std. dev. (3) | Min (4) | Max (5) | Products (6) |
|---|---|---|---|---|---|---|
| Veggies & fruits | 9800 | 0.81 | 0.39 | 0 | 1 | 164 |
| Edible oils | 6480 | 0.69 | 0.46 | 0 | 1 | 135 |
| Cereals | 18320 | 0.79 | 0.40 | 0 | 1 | 351 |
| Pulses | 8560 | 0.83 | 0.37 | 0 | 1 | 139 |

Panel (b): Online product availability before and after lockdown

| | Pre-lockdown | | | Post-lockdown | | |
|---|---|---|---|---|---|---|
| Category | Observations (1) | Mean (2) | Std. dev. (3) | Observations (4) | Mean (5) | Std. dev. (6) |
| Veggies & fruits | 5390 | 0.84 | 0.37 | 4410 | 0.78 | 0.42 |
| Edible oils | 3564 | 0.72 | 0.45 | 2916 | 0.65 | 0.48 |
| Cereals | 10076 | 0.79 | 0.41 | 8244 | 0.80 | 0.40 |
| Pulses | 4708 | 0.81 | 0.39 | 3852 | 0.86 | 0.35 |

Panel (c): Mandi arrivals (in tonnes): before and after lockdown

| | Pre-lockdown | | | Post-lockdown | | |
|---|---|---|---|---|---|---|
| Category | Observations (1) | Mean (2) | Std. dev. (3) | Observations (4) | Mean (5) | Std. dev. (6) |
| Veggies & fruits | 968 | 160 | 322 | 880 | 100 | 200 |

*Notes*: Panel (a) shows the mean product availability by category in our data (all cities) for March 1, 2020–April 13, 2020. Panel (b) shows the mean product availability by category before and after the lockdown in our data (all cities). Panel (c) shows the mean of arrivals (in tonnes) in *Mandis* across the cities. The pre-lockdown period is March 1, 2020–March 24, 2020 and post-lockdown period is March 25, 2020–April 13, 2020. The number of days in the pre-lockdown period are 22, after excluding March 11 (day after Holi) and March 22 (national curfew). The number of days in the post lockdown period are eighteen for online data, after excluding March 29 and March 30 (the data were not scraped for these two dates) and twenty for *Mandi* data.

availability and prices in India. The first shutdown started on March 25 (announced on March 24 at 8:00 pm IST). We restrict our analyses to a small time period around the event and use daily data from March 1, 2020 to April 13, 2020. In our baseline specification, we estimate the impact of the lockdown on online product availability and prices using the following equation:[18]

$$y_{jic,t} = \beta_0 + \beta_1 * Lockdown_t + \delta_{jic} + \delta_{dow,c} + \epsilon_{jic,t} \quad (1)$$

where $y_{jic,\ t} \in \{D_{jic,\ t}, ln(P_{jic,\ t})\}$ is a dependent variable. $D_{jic,\ t}$ is a dummy equal to one, if product $j$ of commodity $i$ is available in city $c$ on date $t$, else it is zero. Similarly, $ln(P_{jic,\ t})$ is the log price of product $j$ of commodity $i$ in city $c$ on date $t$. In the case of $D_{jic,\ t}$, equation 1 represents a linear probability model, whereas it represents a linear regression model for $ln(P_{jic,\ t})$. Our primary variable of interest is the dummy variable $Lockdown_t$, which is equal to one if India was under COVID-19 induced national lockdown on date $t$, else it is zero. Thus, $Lockdown_t = 1$ for $t$ after March 24, 2020. We also control for the time-invariant product, commodity, and city heterogeneity through the fixed effect terms $\delta_{jic}$, which captures the average difference in product availability across cities. Differential availability and prices on different days of the week ($dow$) in the three cities are captured through the fixed-effects term $\delta_{dow,\ c}$. The standard errors are clustered at the product level and regressions are weighted to give equal representation to each city.

If the lockdown reduces product availability, $\beta_1$ should be negative for $D_{jic,\ t}$. Here, non-availability indicates that the product went out of stock on that day. In case of log prices, $ln(P_{jic,\ t})$, a positive $\beta_1$ implies that the prices went up during the lockdown period. The above equation cannot provide a reason behind the change in prices. However, it helps gauge the impact on the prices in equilibrium.

[18]All products that were available for less than ten days in the pre-lockdown period were dropped from the analyses because these are likely to be the ones with larger variance in availability. We check the robustness of all the results to incorporating all products and find that the conclusions do not change.

**Table 2. Impact of Lockdown on Online Product Availability and Price**

| Variable | Veggies & fruits (1) | Edible oils (2) | Cereals (3) | Pulses (4) |
|---|---|---|---|---|
| Panel (a): *Availability* | | | | |
| Lockdown | −0.063*** | −0.103*** | −0.000 | 0.039*** |
| | (0.008) | (0.016) | (0.008) | (0.009) |
| R-sq | 0.204 | 0.228 | 0.253 | 0.241 |
| Observations | 9800 | 6480 | 18320 | 8560 |
| Panel (b): *Prices* | | | | |
| Lockdown | 0.007** | −0.008** | 0.024*** | 0.023*** |
| | (0.003) | (0.004) | (0.003) | (0.005) |
| R-Sq | 0.973 | 0.991 | 0.987 | 0.969 |
| Observations | 7928 | 4472 | 14538 | 7134 |
| City × Product FE | Y | Y | Y | Y |
| City × Day of Week FE | Y | Y | Y | Y |

*Notes*: In Panel (a), the dependent variable takes a value one if a product for a given category is available on a day in a city and zero otherwise. The estimates are based on a LPM model and give the impact of lockdown on probability of product availability. In Panel (b), the dependent variable is log (Price) of a product. The variable *Lockdown* equals one for March 25, 2020-April 13, 2020. All regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses.
***p < 0.01.
**p < 0.05.
*p < 0.10.

For the above framework to work and give an unbiased estimate of $\beta_1$, we require that the lockdown was unanticipated. Although there were media reports on the possibility of an economic shutdown, the exact date and stringency measures came as a surprise (refer to the discussion in Background Section 2). Furthermore, we include only twenty days after the first lockdown in our analysis as the later announced extensions of the lockdown were anticipated. Restricting our sample to a narrow window also allows us to reduce seasonality concerns. Last, we also test for pre-trends to support our assumption that the first national lockdown was unanticipated.

We estimate equation 1 separately for the four categories of products as they differ on perishability and can witness differential impacts due to lockdown. First, non-perishables are more likely to be stockpiled by the retailer as well as consumers. Second, the non-perishables can come back in circulation when the supply chains are partially restored, and products can be delivered, albeit with a delay.

Last, we estimate the impact of the lockdown on quantity of commodity arrivals in *Mandis* before and after the first national lockdown using a similar specification:

$$Q_{ic,t} = \beta_0 + \beta_1 {}^{*} Lockdown_t + \delta_{ic} + \delta_{dow,c} + \epsilon_{ic,t} \tag{2}$$

where $Q_{ic,\ t}$ is the inverse hyperbolic sine transformation (Burbidge, Magee, and Robb 1988) of quantity arrivals (in tonnes) of commodity $i$ in city $c$ on date $t$. We use this transformation to account for the possibility of zero arrivals on some dates for certain commodities. The interpretation of the estimates obtained using the inverse hyperbolic sine transformation is the same as those obtained using a natural logarithm transformation of the dependent variable, with the advantage of being defined at zero. Unlike equation 1, here we control for unobserved heterogeneity at the commodity-city level through the term $\delta_{ic}$. A negative sign on $\beta_1$ shows a fall in quantity arrivals of commodities after the lockdown in the primary *Mandis* and is interpreted as a percentage change, given the transformation.

## Results

In this section, we provide our main set of results on product availability and prices.

### *Fall in Average Product Availability in Retail Data*

Table 2 shows the estimation results based on equation 1 for online product availability in Panel (a). Each column reports the results separately for each category of products. We find that the probability of product availability for vegetables and fruits (column (1)) post lockdown falls by 0.063, which is around 8% of their average pre-lockdown availability. The columns (2)–(4) report results for the non-perishable product categories. We find that the availability of edible oils falls significantly by 14%. However, cereals and pulses do not show any fall in the overall availability of products.

The above results show that the average availability falls sharply for vegetables and fruits and edible oils during the lockdown, but did it lead to an increase in their prices? To estimate the effect of the lockdown on online prices, we estimate Equation 1 with the log price of the product as our dependent variable (for days the product was available). These results are reported in Panel (b) of table 2. We find that the prices for vegetables and fruits went up very marginally by around 0.6% (column (1)). For edible oils, we find that their prices fell marginally by 0.8%. On the other hand, for cereals and pulses, we find an average increase of 2% in prices. We also estimate the effect of the lockdown on retail prices using the data collected by the Department of Consumer Affairs (DCA). The details of the data and the estimation are available in Appendix B. We find broadly similar results that are reported in Appendix table B.1, except for restricted set of vegetables and fruits (potato, onion, and tomato).[19]

Overall, the online price increase is low and not commensurate with the fall in availability. This evidence is consistent with previous studies that find little impact of disasters on product prices (Gagnon and Lopez-Salido 2020 and Cavallo, Cavallo, and Rigobon 2014). In our case, it can happen for two reasons. First, the online sellers can have reputation concerns. Similar to Cabral and Xu (2020), it serves the interest of a long-term player to not lose reputation for short-term profits. The online retailer in our case is a long-term player. Second, the online prices are easily monitored. The existing legal framework in India does not explicitly preclude price gouging behavior. However, in the absence of a specific law on price gouging, the government invoked the Essential Commodities Act (ECA). This law allows the government to crack down on black marketing of commodities and hoarding by sellers for essential commodities. This government action could have curtailed price gouging to a certain extent, especially in online markets where prices are easy to monitor.[20]

The above results raise the question about what led to a fall in the availability of vegetables and fruits and edible oils. Change in average demand over this period is unlikely to kick in for online retailers as they generally cater to the middle to upper income segments in India. Also, a reduction in demand can result in a lower stocking up of a product by a retailer, but it is less likely to cause a complete stock-out. We now test if supply chain disruptions can explain this observed fall in product availability.

### *Supply Chain Disruption: Distance to Production Matters*

We hypothesize that supply chain disruptions during the lockdown are likely to be more severe for products that travel long distances to reach the retail markets. It can happen due to increased border control by states as well as a fall in freight services during the lockdown. We directly test for these disruptions for vegetables and fruits and edible oils by calculating distances from production zones for the former and from the nearest manufacturing unit for the latter from each of the three cities in our analyses. For each edible oil sold in our cities, we hand collect the nearest manufacturing unit for a given product–city combination. We then calculate the road distance (in kilometers) from the nearest manufacturing unit to each city.

In the case of edible oils, the explanatory variables include an indicator for the lockdown period and its interaction with inverse distance to the nearest manufacturing unit. The results are reported in column (1) of table 3. The coefficient on the interaction term is negative and significant. It shows that as distance decreases, there is an exponential increase in the availability of a given edible oil product and that there is no fall in availability of edible oils, which are manufactured within the city.

We undertake a similar analysis for fruits and vegetables but at the commodity level. To measure how near a city is to the production zone of a commodity, we combine information on state-level production (available for nineteen out of twenty-two commodities) with the road distance for each city from each state of India. We construct a *Near Index*$_{ic}$ for each commodity–city pair. The index is

[19]Narayanan and Saha (2020) also look at changes in food prices in India during the lockdown using commodity level price data collected by the government agencies. However, they do not look at changes in the availability of goods.

[20]See: The Economic Times Report.

**Table 3. Impact of Lockdown on Online Product Availability (Heterogeneity by Distance to Production)**

| Dependent variable | Edible oils Online data *availability* (1) | Veggies & fruits Online data *mean availability* (2) |
|---|---|---|
| Lockdown | −0.109*** | −0.082*** |
| | (0.016) | (0.015) |
| Lockdown × Inverse Distance | 0.103** | |
| | (0.000) | |
| Lockdown × Near Production | | 0.040* |
| | | (0.021) |
| Estimate | | −0.041 |
| P-Value | | 0.008 |
| R-sq | 0.232 | 0.188 |
| Observations | 6040 | 1760 |
| City × Product FE | Y | |
| City × Day of Week FE | Y | Y |
| City × Commodity FE | | Y |

*Notes*: The dependent variable in column 1 takes a value one if a product for edible oils is available on a day in a city and zero otherwise, because information on distance of the manufacturing center from the cities is available for each product within edible oils. The dependent variable is the fraction of products available for sale on a day in a city for a given commodity under vegetables and fruits in column 2, because distance to production locations is available at the commodity level for vegetables and fruits. The variable *Lockdown* equals one for March 25, 2020–April 13, 2020. The distance in column (1) is measured in kilometers. The *NearProduction* variable is defined in Section 3 and is available for sixteen out of eighteen commodities. Regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses for edible oils. Robust standard errors in parentheses for vegetables and fruits because the number of commodities are small (18).
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.10$.

calculated by weighting the inverse road distance of each state capital, $s$, from city $c$, by the production contribution of that state in commodity $i$:

$$(3) \quad Near\,Index_{ic} = \sum_{s=1}^{S} \frac{1}{d_{cs}} Production_{is}$$

where $d_{cs}$ is the distance between city $c$ and state $s$. $Production_{is}$ is the proportion of production of commodity $i$ from state $s$, and sums to one across all states.[21] Our measure is similar to the one used by McArthur and McCord (2017), who use an inverse cost–distance measure across countries for capturing access to fertilizers. Finally, we categorize the commodity as having a production center near to the city (*Near Production = 1*) if the *Near Index* is above the median value for all commodities in a given city, else it is zero.

Because the information on distance to production zones is available for vegetables and fruits only at the commodity level, we use mean daily product availability for each commodity as our dependent variable.[22] The explanatory variables include an indicator for the lockdown period and its interaction with the *Near Production* zone indicator. Our identification here comes from a between commodity comparison. The results for this specification are shown in table 3, column (2). We again find that the mean availability falls during the lockdown, as the coefficient on lockdown is negative. However, the coefficient on the interaction term is positive and significant. It shows that the fall in mean product availability for a commodity is lower (almost by half) if it is produced relatively near the city. The above results show that the products which travel farther were more likely to go out of stock with the online retailer. Next, we test if quantity arrivals for commodities at the farm-gate also witness a similar fall.

[21]Because our distance measures are within India (domestic agricultural trade is large in India), we assume that per kilometer cost of transport is the same across cities for each commodity and hence is a scaling factor, which can be omitted.

[22]For example, our data have a measure of production of cabbage in each state and not for each product within cabbage. If one out of five types of cabbage is available on a given day, the dependent variable gets a value equal to 0.2.

**Table 4. Impact of Lockdown on Commodity Arrivals in *Mandis* (Vegetables and Fruits)**

| | *Quantity arrivals* | |
|---|---|---|
| Variable | (1) | (2) |
| Lockdown | −0.201*** | −0.421*** |
| | (0.055) | (0.088) |
| Lockdown × Near Production | | 0.418*** |
| | | (0.122) |
| R-sq | 0.819 | 0.803 |
| Observations | 1848 | 1596 |
| Estimate | | −0.003 |
| P-value | | 0.972 |
| City × Commodity FE | Y | Y |
| City × Day of Week FE | Y | Y |

*Notes*: The dependent variable is an inverse hyperbolic sine transformation of quantity arrivals (in tonnes) on a day for a given commodity across all *Mandis* in a city. The variable *Lockdown* equals one for March 25, 2020–April 13, 2020. The *NearProduction* variable is defined in Section 3 and is available for nineteen out of twenty-two commodities. *Mandi* arrivals is available only for two cities (Delhi and Kolkata) because data for Chennai were unavailable for this period. In *Mandi* data, each city has equal observations, because each commodity is observed for each city, hence the results are unweighted. Robust standard errors in parentheses.
***p < 0.01.
**p < 0.05.
*p < 0.10.

### *Fall in Quantity Arrivals in Mandis*

Table 4, column (1) reports the estimation results for the data on *Mandi* arrivals and shows that the quantity arrivals for vegetables and fruits fall by 20% in these cities. As expected, the percentage fall in quantities of arrivals at the farm-gate is larger than the increase in product stockouts at the retail level. The latter is an extreme event and occurs when zero quantity of a product is available. Thus, the product stockouts in online retail capture only the extreme disruption in food supply chains.[23]

Next, we estimate if the fall in quantity arrivals at the farm-gate, that is, *Mandis*, also varies by the distance to their production zones. The results presented in column (2) of table 4 show that quantity arrivals in *Mandis* fall by 42% post the lockdown for commodities that are produced farther. However, there is no fall in the arrivals for commodities that are produced near the retail centers. The coefficient on the interaction term is positive and significant, and nullifies the negative impact due to lockdown on commodities produced near the cities. The results on distance are again stronger in *Mandi* data, as the online data captures the mean availability on the extensive margin, an extreme fall in availability. Overall, our results show that long distance freight disruptions are behind the observed fall in commodity supplies (wholesale level) that eventually lead to product stockouts at the retail level.

## Robustness

In this section, we present robustness checks for our main results.

### *No Pre-trends in Availability and Persistence in Fall*

Our main results show that products like vegetables and fruits and edible oils are more likely to go out of stock. However, the lack of cold storage facilities and seasonal availability of certain commodities, more likely for vegetables and fruits, can also lead to a change in product availability over time. Because we restrict our analyses to a narrow time window before and after the lockdown, it partially alleviates this concern. Nevertheless, we estimate the change in the week-wise availability of products taking the week of March 1–7 (W1) as the baseline. Unlike our main specification, we now allow for a longer time series to evaluate if the product availability reverted to its level in the pre-lockdown period.

Figure 2, Panel (a), plots the weekly coefficients for vegetables and fruits using online data. The period between the red and blue lines corresponds to the first lockdown. We find that product availability sharply reduces after the lockdown with no pre-trends before the lockdown. Panel (b) plots the weekly coefficients for vegetables and fruits with *Mandi* data. We again find that the fall begins only post the lockdown. These results also support the validity of our assumption that the first lockdown was unanticipated. Notably, the fall in *Mandi* arrivals occurs a week before the product stockouts happen in the online retail market. This clearly hints at disrupted supplies to the city, leading to product stockouts. Also, if anticipation were driving our results, then the farmers should have increased supplies in the wholesale market, fearing a lockdown in the near future. However, we see no increase in farm-gate arrivals before the lockdown. Once again, it reduces concerns regarding the anticipation of the first lockdown.

[23] We also examine the price data for the limited set of commodities in *Mandis* from Kolkata and do not find an increase in farm-gate prices during the first lockdown.

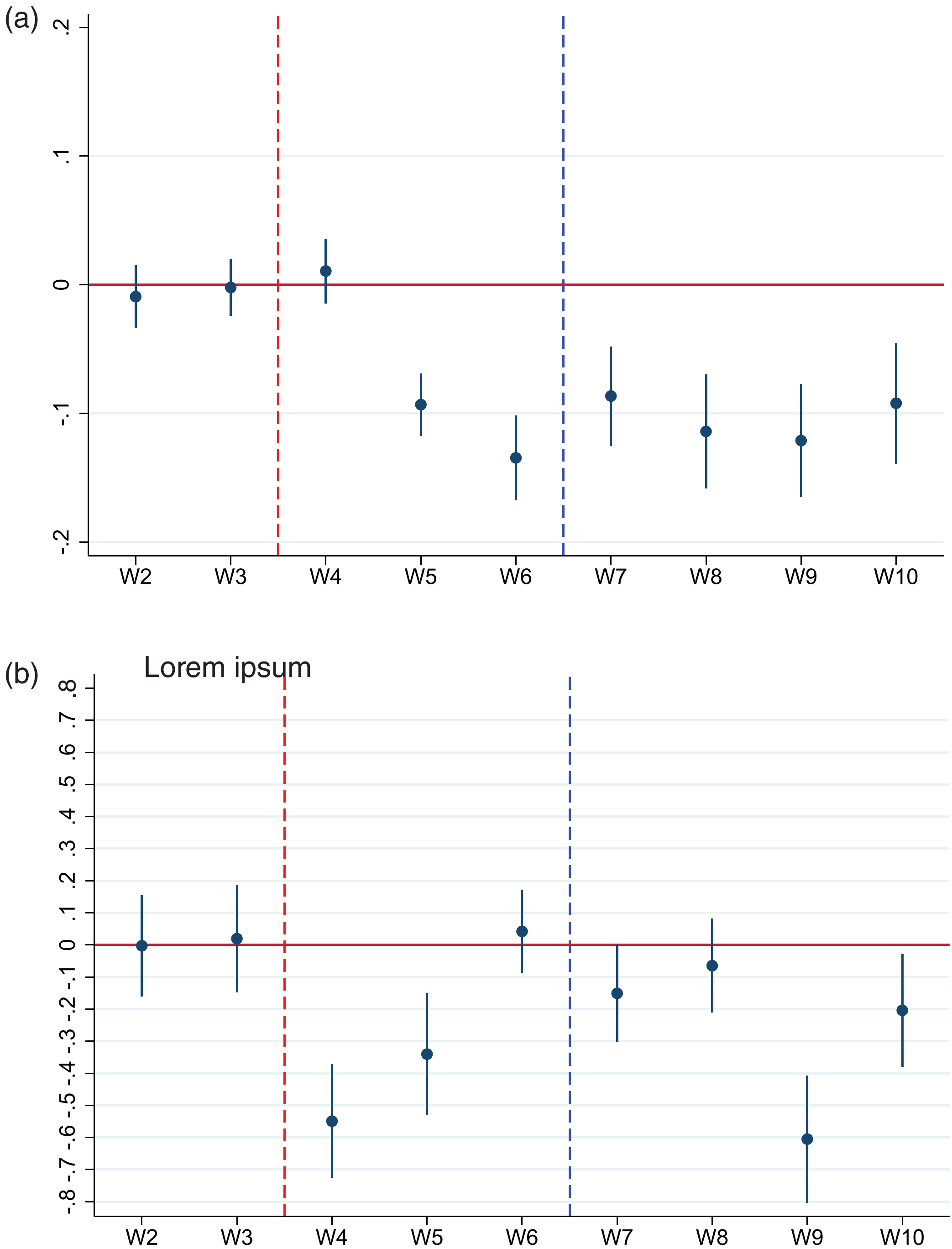



**Figure 2. Pre-trends and persistence in vegetables and fruits (2020)**

*Notes*: The figures plot the weekly coefficients and their 95% confidence intervals. In Panel (a), the dependent variable takes a value one if a product is available on a day in a city and zero otherwise. In Panel (b), the dependent variable is an inverse hyperbolic sine transformation of quantity arrivals in *Mandis* (in tonnes) for a commodity. The red (blue) dashed line is the week of the first lockdown (end of first lockdown). Sundays are removed from the weekly analyses because product availability shows large fluctuations on Sundays due to *Mandi* closures. W1 = March 1–7, W2 = March 8–14, W3 = March 15–21, W4 = March 22–28, W5 = March 29–April 4, W6 = April 5–11, W7 = April 12–18, W8 = April 19–25, W9 = April 26–May 2, W10 = May 3–10. The regressions are weighted to give equal representation to each city and 95% confidence intervals are plotted using clustered standard errors (at product level) for online data. 95% confidence intervals are plotted using robust standard errors for *Mandi* data.

Figure 3, Panel (a) for edible oils also shows that the product availability for oils falls only after the lockdown, and there are no pre-existing negative trends as the coefficients for week 2 and week 3 are not statistically different from those in week 1.

We now examine the persistence in the effects on online product availability, and wholesale arrivals post the first lockdown. Figure 2 (Panel (a)) for online retail shows that the availability of vegetables and fruits does not improve even after week 6 (end of the first lockdown) and continues to remain at a lower level. For *Mandi* data, in Panel (b), we find that the percentage fall in wholesale arrival quantities reduces toward the end of the first lockdown, but the gains are quickly reversed thereafter. These results for perishables show that their supply chains continue to remain disrupted. On the other hand, the online availability of edible oils recovers after week 6 (figure 3, Panel (a)). A delay in transportation does not lead to spoilage of non-perishables like edible oils, allowing for their revival in the later period. The recovery in the availability of edible oils also shows that a fall in demand cannot explain our results. Any fall in demand should have only increased over time as incomes fell due to the lockdown. Next, we rule out that no such trends existed in 2019.

### *No Seasonality in Availability*

We implement a placebo test using data from 2019 to check for the impact of seasonality on availability. We consider the period from March 1–April 13, 2019, with a placebo lockdown on March 25.[24] The weekly coefficients on vegetables and fruits are plotted in figure 4. Panel (a) plots the coefficients for the online retail data and panel (b) plots it for the *Mandi* data. It can be clearly seen that the seasonality patterns in 2019 do not mimic the patterns in 2020, for the same time period. It thus eliminates seasonality as the main reason behind our results on vegetables and fruits. Similar results follow when we test for seasonality in the availability of edible oils in online data. Panel (b) of figure 3 plots the coefficients for edible oils availability in 2019, which shows no change in availability over time.

### *Heterogeneity by Initial Listing*

Last, we check for heterogeneity in online availability as a function of the initial listing of products. For vegetables and fruits, we classify a product $j$ within commodity $i$ and city $c$ as *high listing* if its pre-lockdown availability is above the median availability for products within $i$ and city $c$, and *low listing* otherwise. For edible oils, pulses, and cereals, *high listing* is defined within each category–city pair. The supply chains for *high listing* products are likely to be more resilient as the retailer can have a stronger relationship with the trader or supplier of these products. Also, the retailer is likely to have larger stocks of *high listing* products, especially the non-perishables. In both cases, we expect that the *low listing* products will suffer a larger decline in availability during the lockdown as the retailer finds it difficult to procure them when stocks run dry. On the other hand, if demand for *high listing* products increased more post the lockdown due to the possibility of greater consumer preference for these, then we expect that the *high listing* products will suffer a larger decline in availability during the lockdown due to panic buying.[25]

To test this hypothesis, we modify equation 1 to include an interaction term of the lockdown period with the *high listing* product indicator. We report the results for this regression in table 5. The results show that across different types of goods, perishables and non-perishables, the *high listing* products faced a lower reduction in availability during the lockdown. The coefficient on the lockdown indicator is negative, whereas on the interaction term it is positive and significant for all categories. This table also explains why we saw no impact on aggregate availability of cereals and pulses in table 2. The greater availability of *high listing* products under cereals and pulses nullified the negative impact on availability due to stockout of *low listing* products.[26]

However, could the increased availability of *high listing* products reflect an increased

[24]For the online retailer, the data for 2019 is only available for the city of Delhi. The data scraping during this period could not be done for Kolkata and Chennai until mid-April 2019 due to structural changes to the retailer's website.

[25]For a few commodities, all products were available on all days before the lockdown, in that case all products are coded as *high listing*. The *low* and *high listing* products have an average 15%–20% difference in availability in the pre-lockdown period. Our classification thus captures only a relative strength of the retailer–supplier relationship. Even the *low listing* products in our sample have around 70% availability in the pre-period.

[26]We also test robustness of our results to other characteristics of fruits and vegetables, and find similar results. We report these results in Appendix table C.1.

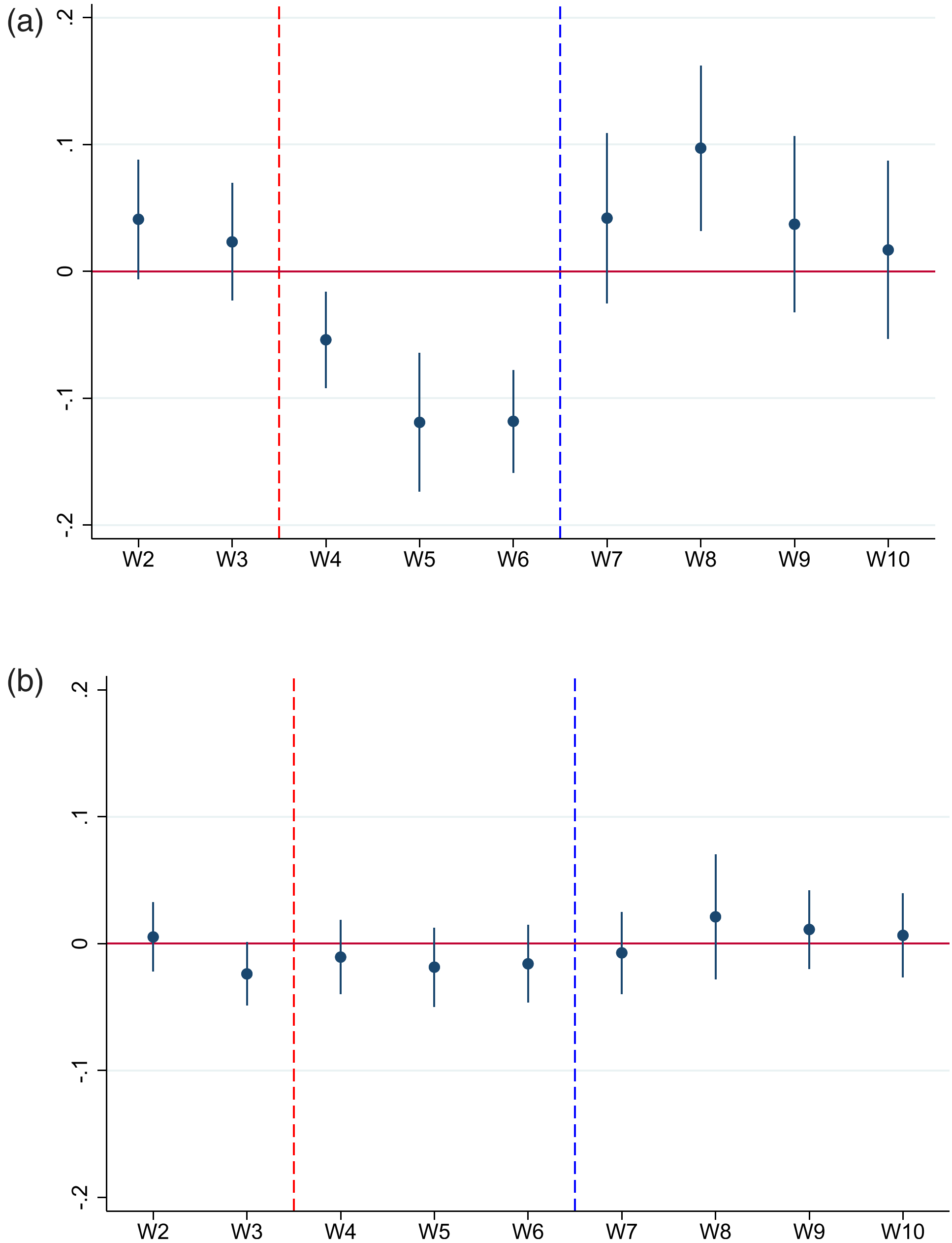
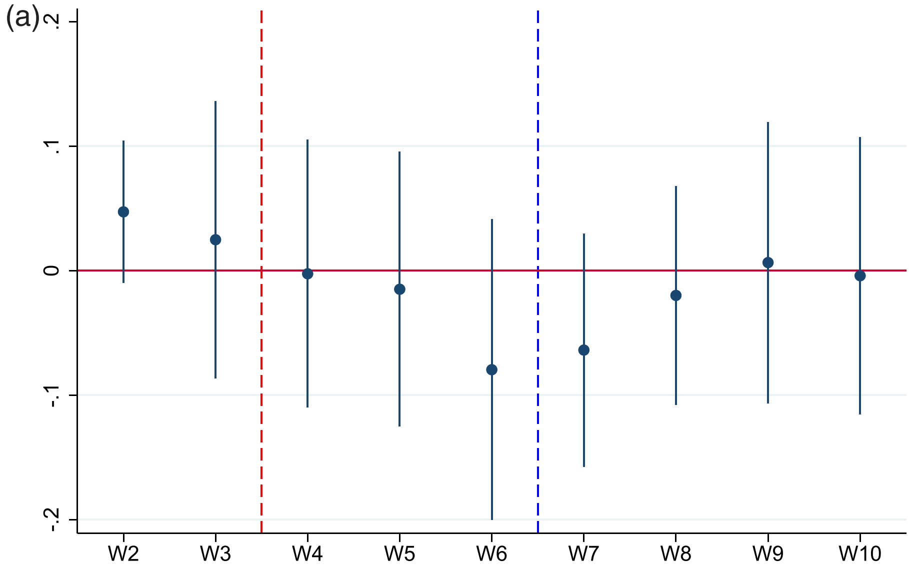



**Figure 3. Persistence and seasonality for edible oils**

*Notes*: The figures plot the weekly coefficients and their 95% confidence intervals. In both panels, the dependent variable takes a value one if a product is available on a day in a city and zero otherwise. The above graphs plot the weekly effects for the year 2020 (Panel (a)) and the year 2019 (Panel (b)) using the same set of dates (March 1–May 10). The red (blue) dashed line is the week of the first lockdown (end of first lockdown). We draw red and blue line corresponding to the same weeks in 2019 in Panel (b). Sundays are removed from the weekly analyses because product availability shows large fluctuations on Sundays due to Mandi closures. W1 = March 1–7, W2 = March 8–14, W3 = March 15–21, W4 = March 22–28, W5 = March 29–April 4, W6 = April 5–11, W7 = April 12–18, W8 = April 19–25, W9 = April 26–May 2, W10 = May 3–10. The regressions are weighted to give equal representation to each city and 95% confidence intervals are plotted using clustered standard errors (at product level) for online data. In Panel (a) data are available for all three cities, whereas in Panel (b), it comes from Delhi. Clustered standard errors (at product level).

demand for *high listing* products as consumers would want to stock them up during the lockdown? The finding that *high listing* products show a lower fall for both perishables (fruits and vegetables) and non-perishables (oils, cereals, pulses) negates this channel because only non-perishables can be stockpiled.



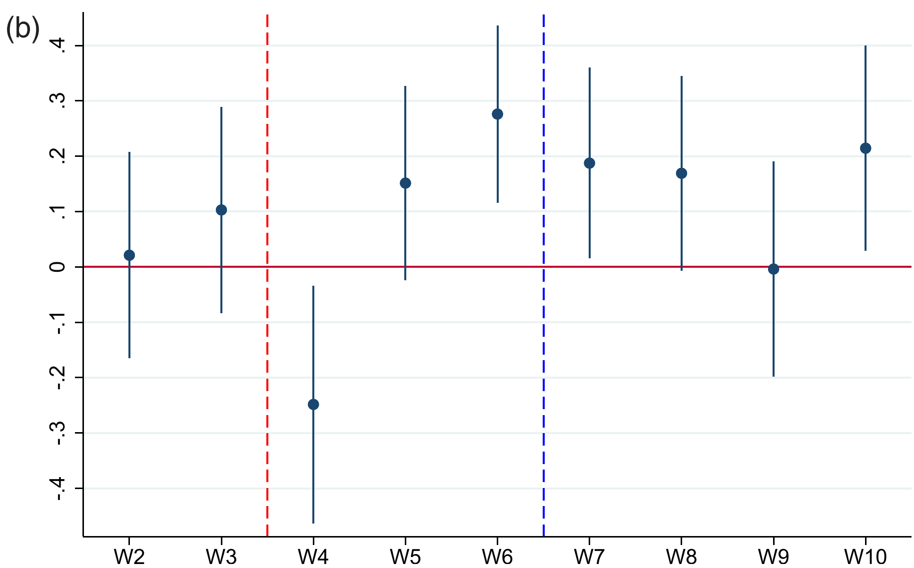




**Figure 4. Seasonality in vegetables and fruits (2019)**

*Notes*: The figures plot the weekly coefficients and their 95% confidence intervals. In Panel (a), the dependent variable takes a value one if a product is available on a day in Delhi. In Panel (b), the dependent variable is an inverse hyperbolic sine transformation of quantity arrivals in *Mandis* (in tonnes) for a commodity. The above graphs plot the weekly effects for the year 2019 using the same set of dates as that in our main analyses but for the year 2019. The red line is the week in 2019 corresponding to the first lockdown week in 2020. The blue dashed line is the week in 2019 corresponding to when the first lockdown ends in 2020. Sundays are removed from the weekly analyses because product availability shows large fluctuations on Sundays due to Mandi closures. W1 = March 1–7, W2 = March 8–14, W3 = March 15–21, W4 = March 22–28, W5 = March 29–April 4, W6 = April 5–11, W7 = April 12–18, W8 = April 19–25, W9 = April 26–May 2, W10 = May 3–10. The regressions are weighted to give equal representation to each city, and 95% confidence intervals are plotted using clustered standard errors (at product level) for online data. 95% confidence intervals are plotted using robust standard errors for *Mandi* data.

## Discussion and Conclusion

This paper quantifies the impact of economic lockdowns to deal with the COVID-19 pandemic on food availability in a developing country setting using data from online retail and primary agricultural markets. We find that online product availability fell by 10% on average, but there was little impact on online prices. This fall in product availability in online retail

**Table 5. Impact of Lockdown on Online Product Availability (Heterogeneity by Initial Listing)**

| Variable | Veggies & fruits (1) | Edible oils (2) | Cereals (3) | Pulses (4) |
|---|---|---|---|---|
| Lockdown | −0.112*** | −0.189*** | −0.062*** | −0.000 |
| | (0.011) | (0.025) | (0.012) | (0.016) |
| Lockdown × High listing | 0.106*** | 0.175*** | 0.141*** | 0.074*** |
| | (0.014) | (0.033) | (0.013) | (0.017) |
| Estimate | −0.006 | −0.015 | 0.079 | 0.074 |
| P-Value | 0.469 | 0.482 | 0.000 | 0.000 |
| R-sq | 0.207 | 0.237 | 0.260 | 0.243 |
| Observations | 9640 | 6480 | 18320 | 8560 |
| Mean availability (Low-listing) | 0.756 | 0.638 | 0.697 | 0.695 |
| Mean availability (High-listing) | 0.937 | 0.813 | 0.912 | 0.917 |
| City × Product FE | Y | Y | Y | Y |
| City × Day of Week FE | Y | Y | Y | Y |

*Notes*: The dependent variable takes a value one if a product for a given category is available on a day in a city and zero otherwise. For vegetables and fruits, *High listing* refers to a higher than median percentage days availability in the pre-lockdown period for a product within a given commodity–city pair. A few commodities having only single products in a city are dropped from the analyses leading to smaller number of observations than the base specification. For edible oils, cereals, and pulses, *High listing* refers to a higher than median percentage days availability in the pre-lockdown period for a product within a given category–city pair. The variable *Lockdown* equals one for March 25, 2020–April 13, 2020. The regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses.
***p < 0.01.
**p < 0.05.
*p < 0.1.

was equally matched by a fall in product arrivals in the wholesale markets, pointing toward a general supply chain disruption.

Finally, using data on product-level manufacturing, we show that the products manufactured far from the retail centers suffered a higher fall in availability. Hence, supply chains during COVID-19 were more fragile for products that travel long distances before reaching their final point of sale. The fall in arrivals in the wholesale markets also highlight that the observed supply chain disruptions would have led to income loss for farmers, especially those producing perishables. Moreover, the effect would have been larger for the farmers located farther from retail centers, that is, those unable to bring their products to the cities due to long distance.

Our findings have three direct policy implications. First, they highlight the importance of warehousing facilities in urban and rural centers in developing countries. We find a large fall in retail product availability in urban centers within a very small time window, primarily driven by producers unable to bring their produce to these centers. A better warehousing infrastructure can build resilience against such supply disruptions in the future for both consumers and producers. Second, and relatedly, swift policy actions that ensure minimum transportation bottlenecks for producers of perishable products must be a policy priority during natural disasters. Third, our work also demonstrates the importance of strengthening procurement pipelines from local producers and growers. Because products procured from far saw a higher decline in availability, robust local supply chains can guard against supply shocks during disasters or pandemics.

More generally, our work illustrates how online data can be used in conjunction with other datasets for real-time policymaking. This is especially relevant during COVID-19 when the official data collection itself has suffered due to the pandemic. However, because our data pertain to urban households that use online shopping, a few caveats are in order. We use data from a large online retailer that can have more resilient supply chains than smaller retailers. Also, we look at online product stockouts. Therefore, our estimates are a lower bound on the overall fall in quantity available in the retail market. This bears out in the agricultural market arrivals data analyses, which shows a much larger fall in commodity arrivals.

## Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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